Patent As Quality Signal in Entrepreneurial Finance: A Look Beneath the Surface*

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Abstract

We examine the value of patents on firms' access to venture capital (VC) using Chinese firms. We find that the patent applications (grants) of firms significantly increase their likelihood of obtaining VC funding in the following year(s), particularly for high-quality patents in high-tech industries. Depending on investment, patent quantity significantly improves the size of VC investment and firm valuation. This effect is pronounced in first-round investment, strong intellectual property protection regions, loose monetary policy, and state/corporate VC. Overall, we support the use of patent as quality signal in attracting entrepreneurial finance outside the U.S. and warrant the conditions it holds.

Keywords: Patent, Venture capital, Signaling, Innovation

JEL Classification: G24, L26, O39

1. Introduction

A number of empirical evidence from the U.S. suggests that patenting activities help entrepreneurial firms gain access to venture capital (VC) (Cao and Hsu 2011, Conti et al. 2013, Hsu and Ziedonis 2013, Hoening and Henkel 2015, Farre-Mensa et al. 2016).

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Young and high-growth firms that seek external financing should communicate quality issues with investors. When making investment decisions, venture capitalists also seek credible quality signals associated with unobservable, growth potential of the firm (Stuart et al. 1999). According to Spence (1973), patents conform well to the conceptualization of a "signal." They are costly to obtain, certified by the government on novelty and non-obviousness, and are exclusive property rights with intrinsic value.

The value of patent in helping entrepreneurial firms finance their growth is an important issue, but only a few studies examined the *conditions* of which this positive effect holds. These conditioning factors are crucial because patents are costly to obtain, not necessarily associated with return, and VC differs in terms of expertise and objective functions. In certain regions, the strategy of using patent as signal is more successful at specific stages of development and macro-economic periods in attracting certain types of VC. Existing studies on patent signal focuses on the U.S., but whether these findings extend to other VC markets requires exploration. This study presents novel evidence from China, which is one of the world's largest technological markets and a hotspot of international venture capital.

China is an important market and a unique laboratory for this test[1]. In 2016, the Chinese patent office received over 1.1 million patent applications, which was almost equal to the total applications received in the U.S., Japan, and Korea. Since 2010, non-U.S. investments accounted for approximately half of global VC investments (of which China is the largest importer); this period also marks considerable improvement in the quality of VC investment data outside the U.S. (Da Rin et al. 2011). As an economy in transition, the different regions of China undergo a process of heterogeneous market development. The venture capital market is characterized by foreign and domestic (state and private), independent, and corporate players. Finally, the Chinese venture capital industry is volatile as a response to global economic conditions and domestic political mandates. These institutional settings provide unique variations that can be exploited.

We start by testing whether the patenting activities (applications and grants) of Chinese firms are important in attracting VC investment. By using data on VC investments and patenting activities of publicly traded Chinese firms from 1998 to 2016 and after conducting propensity score matching, we find robust evidence that the submission of patent application or grant in the present year positively predicts the firms' likelihood of obtaining VC fund in the next year(s). Depending on VC investment, a large quantity of patents is associated with increased investment amount and firm valuation. Further tests indicate that this positive relation depends on patent quality.

What explains this association? We hypothesize that a patent can act as a good signal if it can reduce information friction between VC and entrepreneurial firms. Information asymmetry is likely to be high when the firm is private and is seeking venture capital for the first time. To test this hypothesis, we exploit the fact that venture capitalists typically invest in stages (Tian 2011); we also examine whether this effect is stronger in the first round than in subsequent rounds of VC investment; we find that latter is understandably associated with less uncertainty. Consistent with this conjecture, we find that the positive effect of patents on VC investment is significant only in the first round of investment. We also show that this effect is pronounced in private firms, but diminishes when firms go public.

Patents are intangible property rights and legal safeguard in the product market. The expropriation risk of patents crucially depends on the legal environment that protects intellectual property rights (IPR). We expect that firm patents in regions subjected to piracy rather than the transaction environment of IPR are not valuable to venture capitalists. To test this assumption, we exploit heterogeneities in China's regional IPR protection (Ang et al. 2014); we find that the positive effect of patents on VC investment weakens when firms are located in provinces with low IPR protection.

Venture capitalists may over- or under-react to the signal of firm patents under different market conditions. According to Gompers and Lerner (2004), the venture capital industry is highly volatile. Increased funds flow to VC firms in periods of loose monetary policies. During these periods, VC may be proliferated and compelled to follow the herd in chasing market opportunities (Scharfstein and Stein 1990). A patent signal strategy may be effective in attracting VC under this environment. By contrast, VC tends to be less tolerant to the innovative efforts of firms during periods of capital constraints. Thus, patent signal alone may not be sufficient in attracting investment. We test this possibility by observing the sensitivity of VC to patent signal during periods of loose and tight monetary policy. We find that the positive effect of patents on VC investment is stronger during periods of loose monetary policy than when it is tight.

We then exploit the fact that VC differs in terms of objective functions and expertise, thereby causing heterogeneous sensitivity to the patent signal of firms. For example, China's state-owned venture capital (SVC) has a political mandate to support technological innovations; thus, they are expected to be more patent savvy than, say, return-driven foreign venture capital (FVC), which are doubtful on the value of Chinese patents. By contrast, corporate venture capital (CVC) may have higher industry knowledge and tolerance for failure than independent venture capital (IVC) (Chemmanur et al. 2014). By allowing patent sensitivity to depend on the type of venture capital, we find that SVC is more sensitive to the patent signal of firms than FVC, and CVC is more sensitive to patent quality than IVC.

Our identification relies on the long and random delay between the application and grant dates of patents (Gans et al.; Brav et al. 2016). In our sample, the average time interval from patent application to grant is 4.04 years (medium interval is 3.86 years). The exact timing of a patent grant is not controlled by the applicant or VC, and VC has no superior information to predict the exact date. The timing of patent application is often the outcome of years of research and development. To rule out the alternative explanation that the patenting activities of firms in year t are simply a proxy of the observable innovative capacity of the firm, we use the patent *stock* of firms in year t since incorporation as placebo. We find that the patent stock of firms increases the probability of VC investment, but not the amount of investment and firm valuation.

This study is relevant to several streams of literature. First, we add to the evidence on the signaling role of patents in attracting entrepreneurial finance outside the U.S. Existing studies in the U.S. found that firm patents serve as signal to reduce information asymmetry and enhance the likelihood of obtaining VC funds in specific industries (Engel and Keilback 2007; Hsu and Ziedonis, 2013; Hoening and Henkel, 2015). They also found that the signaling effect of patents decreases in the later round of VC investment (Cao and Hsu, 2011; Conti et al. 2013). Farre-Mensa et al. (2016) found that the approval of first patent application of a startup significantly increases the likelihood of obtaining VC funding in the next three years.

We also shed light on the role of VC in fostering corporate innovation. Prior studies found that VC-backed firms have higher innovation outputs than non-VC-backed firms (Kortum and Lerner 2000; Hirukawa and Ueda 2008); however, these studies did not confirm whether this finding is due to "selection effect" or "treatment effect." Hellman and Puri (2000) showed that companies that pursue innovator rather than imitator strategies are likely to obtain VC. Our study shows that venture capitalists are attracted to the most recent patenting activities. Patent quantity significantly enhances the amount of investment and firm valuation depending on investment.

The present study is related to literature that documents the effect of legal enforcement (Lerner and Schoar 2005; Bottazzi et al. 2009), the debate between corporate and independent VC (Fulghieri and Sevilir 2009; Chemmanur et al. 2014), and foreign versus domestic VC (Nahata et al. 2014) on investment. This study is also related to studies on the behavioral bias of VC to over-reaction to investment opportunities during market heat-up (see Gupta 2000).

The rest of this study proceeds as follows. Part II describes our sample data and variables. Part III presents the empirical results. Part IV shows the results of robustness test. Part V provides the conclusion.

2. Sample and Data

2.1 Data Source and Sampling

Our sample of publicly traded firms includes firms eventually listed in the mainboard (Shanghai and Shenzhen), small and medium enterprise (SME) board, growth enterprise board (together termed "A-share firms"), and National Equities Exchange and Quotations System (NEEQ). We present the results for A-share firms and NEEQ firms respectively because these two types of firms differ in important ways. To illustrate, the Chinese government established the NEEQ system in 2012 with the objective of creating a market for shares of young and not-yet-profitable firms. To be eligible for quotation on the NEEQ, firms need two-year subsistence history, a well-defined business plan, sound corporate governance mechanism and clear equity structure, and recommendation and supervision by a licensed brokerage. The two exchange modes of NEEQ stocks are negotiated transfer and market making, which hinder market liquidity. In short, NEEQ firms are likely to mirror young and high-growth firms.

Our objective is to generate a dataset on patenting and VC investment of A-share and NEEQ firms. To achieve this, we merge two typical datasets with CSMAR. VC investment data come from the *CVSource* database provided by ChinaVenture. *CVSource* includes explicit time, amount, participating funds, and development stage of investees of every VC investment event since 1990s. We use these data to identify VC-backed firms listed on A-share or NEEQ from 1998 to 2016. The patenting activities of firms are collected from the *State Intellectual Property Office of the P.R.C (SIPO) patent information disclosure*. *SIPO* records all patent applications and grants for individuals and organizations in China, including their type and properties. We also complement patent information with *China Listed Firm's Patents Research Database* in *CSMAR*.

Given that lack of a unique firm identifier of VC investment data from *CVSource* as well as data of patent applications or grants from *SIPO*, we use a matching method to assign the stock code to firm which is VC-backed and firm with patenting activities based on abbreviated firm names and full firm names matching. More detailed matching process is available in the online Appendix.

Types of VC are manually collected from the *Yearbook of Venture Capital Development in China* and *List of Characteristics of Venture Capital Institutions* in *CVSource*. We acquire data on regional Intellectual Property Rights (IPR) protection and monetary policy from the *China Statistical Yearbook.*

We further exclude finance and insurance firms and insolvent firms (LEV>1) during the sample period, ST/PT firm-year observations, and observations with missing variables. Finally, we obtain 27,238 A-share firm-year observations, wherein 1,005 obtained VC investment in Year (t+1) and 10,103 NEEQ firm-year observations, of which 867 obtained VC investment in Year (t+1).[2]

2.2 Variable of Interest and Controls

The main variables of interest are patenting activities. Based on literature, (e.g., Cao and Hsu 2011, Hsu and Ziedonis 2013, Hoenen et al. 2014, Brav et al. 2016), we measure *PatentApply* and *PatentGrant* as the total number of successful patents applications of invested firm and patents granted to invested firm by *SIPO*. To explore whether the patenting activity of firms affect VC investment, we use two dummies in the analysis, namely, *ApplyDum* and *GrantDum*. The patent dummies are equal one if the invested firm filed (was granted) at least one successful patent in the present year and zero otherwise.

Our main dependent variables include the *Likelihood of Obtaining VC Funds* (*Prob(VC)*), *Amount of Venture Capital Funds Obtained* (*VC_Amount*), and *Firm Valuation* provided by VC institutions after investment (*VC_Valuation*). *Prob(VC)* is a dummy variable that is equal to one if the firm obtains VC funds in Year (t+1). *VC_Amount* is the natural logarithm of one plus total amount (in￥100 million) invested in the A-share firms by VC institution conditional on obtaining VC funds (in￥0.01 million in the NEEQ sample). *VC_Valuation* is the natural logarithm of one plus total valuation (￥100 million) of invested A-share firms provided by VC institution conditional on firms that obtained VC funds (in￥1 million in the NEEQ sample).

We first conduct probit regressions, wherein the dependent variable is *Prob(VC)* in Year (t+1). We then use OLS regressions to examine the relation between *VC_Amount* / *VC_Valuation* and patenting activities, which takes into account two explanatory variables of interest, namely, patent applications and patent grants.

We include an assortment of firm and industry characteristics following existing research on the determinants of VC financing (e.g., Gompers et al. 2008, Tian 2011, Hsu et al. 2014, Bottazzi et al. 2016, Tian and Ye 2017). *SIZE* is the natural logarithm of book value of total assets in year-end; *LEV* is the ratio of total debt to total asset, which represents financial condition; *TobinQ* is the growth opportunity measured by the ratio of the sum of firm's market value of equity plus book value of debt divided by total assets; *Age* is the natural logarithm of one plus the number of years since incorporation; *OperationRisk* is the standard deviation of ROE in the past three years, which represents fluctuation level of operation; *State* is equals to one if the firm is a state-owned enterprise; *ROA* is the profitability measured by the ratio of net profit to total assets; *HighTech* is equal to one if the firm belongs to technology-intensive industries[3], *StageGrowth1* is equal to one if the firm is in seed and development stage upon obtaining VC investment; *StageGrowth2* is equal to one if the firm is in the expansion stage upon obtaining VC investment; *Syndicate* is the total number of VC firms that participate in the investment.

3.3 Summary Statistics and Propensity Score Matching

Table 1 presents the summary statistics of firms from A-share and NEEQ in the estimation sample. A-share firms are bigger, older, and less volatile than NEEQ firms. In the A-share sample, 44.4% of observations have patent application, whereas 23.0% have granted patent, which are both larger than corresponding ratio in NEEQ sample. A large variation exists among firms on quantity of patent applications and grants. In the sample, 4.1% of A-share firm-year observations receive venture capital in the next year, whereas the ratio for NEEQ firms is 8.5%. The amount of VC investment also varies widely.

[Insert Table 1]

The endogeneity issue, wherein better firms have active patenting activities and strong possibility to attract VC funds, should be addressed to determine whether patents help firms obtain VC financing. In this study, we use propensity score matching (PSM) method to control observable firm characteristics for patenting and similar but non-patenting firms. We first construct a probit model based on all observations in the sample. The dependent variable is equal to one if the firm has patent applications or grants in the current year and zero otherwise. Following previous literature (Chemmanur et al. 2014; Guo and Jiang 2013), we use a series of controls as matching dimensions, which include ownership type (*State*), size (*SIZE*), financial condition (*LEV*), profitability (*ROA*), growth opportunity (*TobinQ*), firm age (*Age*), asset tangibility (*PPE*), and R&D investment (*R&D*). *PPE* is measured by the ratio of inventory plus fixed assets in total asset. *R&D* is the total research and development investment, which includes capitalization in intangible asset and expenditure in current profit and expense. We then use the propensity scores obtained from the first step to perform Kernel matching (one to many) and identify matched sample from that of firms with (treatment) and without (control) patenting activities. Finally, we conduct the paired T-test of VC investment variables on treatment and control firms.

Table 2 shows the T-test results of the two matching samples with similar firm characteristics with patenting activities in Year *t* or not. We find that firms with patent applications or grants in Year *t* have higher likelihood of obtaining VC funds. Specifically, A-share firms with patent applications in Year t have higher probability of 3.8% of obtaining VC in Year (*t+1*), whereas firms with patent grants have a higher probability of 4.0% of obtaining VC funds in next year. This finding provides preliminary evidence that patent-active firms are more favorable to venture capitalists. However, we do not find prominent difference of *Prob(VC)* between treatment and control group in the NEEQ sample.

[Insert Table 2]

3. Empirical Results

3.1 Baseline Results

Table 3 reports the results of the regression that examines the effect of firm patenting activities on the likelihood of obtaining VC funds in the next year.[4] In A-share sample, the patenting activity of firm measures has a significantly positive effect, which has a bigger coefficient of dummy variables than count measures (pass the Chow test). One plausible explanation for this finding is the probability of obtaining VC funds, wherein the symbolic value of *having* any patent application (or grants) is a larger signal than the *number* of firm patents. The coefficient of *ApplyDum* is 0.489, which indicates that, all else being equal, firms with patent application in Year t has 3.64% higher probability of obtaining VC funds in Year (t+1), relative to propensity score matched firms with no applications. This result shows about 140% increase over 2.6% unconditional likelihood of obtaining VC funds in firms without patent applications. The coefficient of *GrantDum* is 0.380, which indicates that the patent granted by SIPO will add to the likelihood of 3.31% of obtaining VC funds. This finding represents about 103% increase over 3.2% unconditional likelihood of obtaining VC funds in firms without patent grants. The marginal effects of *PatentApply* and *PatentGrant* are respectively 0.18% and 0.20%. In the NEEQ sample, all patent variables have a significantly positive coefficient. *ApplyDum, PatentApply, GrantDum, and PatentGrant* have marginal effects on the Prob(VC) of 2.39%, 2.04%, 1.42%, 0.84%, respectively. Overall, patent activities have a positive effect on *Prob(VC)* in the next year.

The signs of coefficients on other control variables are consistent with the prediction in A-share sample, that is, firms with high ROA and Tobin's Q, longer history, and connected to high-tech industries are likely to obtain VC funds, whereas state firms and firms with high operational risk are less likely to obtain VC. Venture capitalists prefer younger NEEQ firms, but other controls in the regressions of NEEQ sample are almost insignificant.

[Insert Table 3]

Table 4 shows the results of the effect of patents in Year *t* on the *VC_Amount* in Year (t+1). We find that the number of patent applications and grants have a significantly positive effect in both samples. One standard deviation increase in *PatentApply* (*PatentGrant*) in Year *t* increases *VC_Amount* in Year (t+1) by 4.1% (3.1%) and 2.1% (0.8%), respectively, in the A-share and NEEQ samples. Moreover, the coefficients of controls show that venture capitalists are willing to increase their investment in older firms with large size, high growth opportunities, and those at the mature development stage.

[Insert Table 4]

Table 5 presents the effect of patenting activities in Year t on the *VC_Valuation* in Year (t+1). In the A-share sample, the coefficients of *PatentApply* and *PatentGrant* are both positive and significant. The one standard deviation increase of *PatentApply* and *PatentGrant* will result in 6.7% and 4.7% growth of *VC_Valuation*. However, in the NEEQ sample, the effect is insignificant on *PatentApply* and negatively significant on *PatentGrant*. We attribute this surprising result to the illiquid nature of the NEEQ market. Venture capitalists consider the high expected transaction cost (Amihud and Mendelson 1986; Acharya and Pederson 2005) to transfer shares on the NEEQ market. Although VCs are willing to increase investment size following the active patenting activities of firms, they discount firm value to compensate for illiquidity risk.

[Insert Table 5]

3.2 Sensitivity of Venture Capitalists to Patent Quality

We employ three novel patent quality metrics, namely, *ClaimCount*, *ElementCount*, and *CitationCount*, to determine whether venture capitalists differentiate high versus low quality patents[5]. We performed two tests. First, we replace the patent measures in fundamental analysis with three quality indicators and restrict the research sample into firms with patents. Second, we divide the whole sample into subsamples based on patent quality level and re-run the baseline tests using different subsamples.

[Insert Table 6]

Panel A of Table 6 shows the relation between patent quality and *Prob(VC)*. We did not find a significant impact of patent quality in Year t on *Prob(VC)* in Year (t+1) in both samples. Panel B shows the results of the effect of patent quality on *VC_Amount* in Year (t+1) and *VC_Valuation in* Year (t+1). We did not find significant effect, except for *CitationCount* when the dependent variable is *VC_Valuation* in Year (t+1). In summary, evidence suggests that venture capitalists do not recognize patent quality when choosing potential investees.

[Insert Table 7]

Table 7 investigates whether the positive effect of patent quantity on *Prob(VC)* depends on patent quality. We divide the whole sample into two groups. The sample with *ClaimCount* larger than industry-year median, or *ElementCount* smaller than industry-year median, or *CitationCount* larger than industry-year median is defined as *High Patent Quality* group; the rest is defined as the *Low Patent Quality* group. We find that the positive effect of *PatentApply* on *Prob(VC)* is only pronounced when the patents of potential investee are of high-quality as measured by *ClaimCount.* By contrast, *PatentGrant* has a more pronounced effect when patents are of high quality measured by *ClaimCount*, *ElementCount* and *CitationCount.* In summary, evidence suggests that high quality patents can strengthen the positive effect of patent quantity on obtaining VC investments in high-tech industries.

3.3 Investment Round

To the extent that patenting activities mitigate information frictions between the firm and VC, we expect that such an effect will diminish as information asymmetry decreases. Following literature (e.g., Hoenen et al. 2014; Hoenen and Henkel 2015), we test whether the positive effect of patenting is stronger in earlier rather than later rounds of investment. To achieve this objective, we partition the investee sample into two groups. When the invested firm obtains VC funds for the first time since establishment, we identify the investment round as the *First Round*, otherwise the *Later Rounds*. We rerun the baseline test on *VC_Amount* and *VC_Valuation* using the two groups in the A-share and NEEQ firms, respectively. In the untabulated results, we find that the coefficients of *PatentApply* and *PatentGrant* are only significantly positive in the *First Round* group in both A-share and NEEQ firms.

3.4 Protection of Intellectual Property Rights (IPR)

Patents are exclusive property rights whose value crucially depends on the legal environment that protects IPR. Ang et al. (2014) found a large difference on IPR protection across Chinese provinces. We expect firm patents to be of little value to VC in regions subjected to piracy rather than to a transacting environment of IPR. Following their approach, we use the size of technological market as proxy for IPR protection, which is measured as the percentage of provincial transaction volume of technology transfer to a province's GDP. This proxy is a comprehensive index that covers the preference of counterparties, utility evaluation, and the trading environment in the technology transfer. We define *LowIPR* as a dummy variable that is equal to one if IPR protection in the firm's home province is less than the median of all provinces across the country in a particular year. Table 8 reports the results. The coefficient of the interactions of patenting activities and *LowIPR* are almost significantly negative. Results indicate that the provincial low IPR negatively affects the patent sensitivity of VCs.

[Insert Table 8]

3.5 Monetary Policy

We then examine the impact of monetary policy on the patent sensitivity of VC. We define loose or tight monetary policy using the difference between the growth of money supply (M2) and that of economic development plus inflation[6]. Our working hypothesis states that: When money supply is relatively high in the market, VC obtains more funds at disposal and is therefore highly tolerant to the innovation efforts of firms. Other VCs follow suit and collectively become more responsive to the patenting signal of firms. By contrast, when the whole market is tight on liquidity, VC faces financial constraints and is inclined to invest in projects with shorter payback period. We rerun the baseline test on *Prob(VC), VC_Amount,* and *VC_Valuation* in A-share and NEEQ firms using subsamples during tight and loose monetary policy period.

In the untabulated results, we find that the relationship between the patenting activities of firms and *Prob(VC)* is more pronounced during loose monetary policy periods. Coefficients of patenting counts on *VC_Amount* and *VC_Valuation* are also significant only during periods of loose monetary policy. The only surprising result is on the *VC_Valuation* for NEEQ firms, which is negatively related to the patenting signal of firms during loose monetary policy. Similar to our discussion in the baseline results, we attribute this result to the illiquidity risk that VCs need to compensate for their valuation of NEEQ firms. Overall, our evidence is consistent with Scharfstein and Stein (1990) on the herding behavior of investors during hot market, which argues investors may simply mimic the investment decisions of others that under certain circumstances, thereby ignoring substantive private information.

3.6 Type of Venture Capital and Patent Sensitivity

Panel A of Table 9 shows the effect of the type of VC ownership on *VC_Amount* and *VC_Valuation*. Our benchmark of comparison is state-owned VC (SVC) versus foreign-owned VC (FVC). SVC is a dummy variable that is equal to one if the VC is state-owned[7], and zero if VC is foreign-owned. We hypothesize that SVC has a political mandate to support technological innovations and, thus, expected to be more patent savvy than, say, FVC, which is driven by firm growth. Consistent with this conjecture, we find that the significant coefficients of *PatentApply*SVC* and *PatentGrant*SVC* are positive when the dependent variable is *VC_Amount* in Year (t+1). Despite the fact that the few coefficients of patent counts are negative, the interactions' coefficients are positive and exceed their absolute value. When the dependent variable is *VC_Valuation*, only *PatentGrant*SVC* in the NEEQ sample has a positive effect. To some extent, this result shows that state-owned VC are more sensitive to patents due to their role of fostering innovation required by the government. Although this behavior is not necessarily value-maximizing for the shareholders, it is perfectly consistent with the objective function of SVC to fill a market failure of early-stage funding gap for technology-intensive firms and the career concern of SVC managers.

[Insert Table 9]

Panel B of Table 9 shows the effect of VC *structure* on *VC_Amount* and *VC_Valuation*. Our benchmark of comparison is independent venture capital (IVC) versus corporate venture capital (CVC).[8] Compared with IVC, CVC and its parent company may possess more industrial knowledge to understand the underlying patent and greater tolerance for failure and better capability to find synergy of the entrepreneurial firm with their existing operation (Chemmanur et al. 2014). Therefore, conditional on investment, we expect CVC to be highly sensitive to the patenting signal of firms in *VC_Amount* and *VC_Valuation*. All coefficients of interactions (*PatentApply*IVC*, *PatentGrant*IVC*) are negative when the dependent variable is *VC_Amount* in Year (t+1). This finding indicates that IVC is less sensitive to the patenting activities of firms than CVC. This correlation also exists in NEEQ sample when the dependent variable is *VC_Valuation*.

4. Robustness Tests[9]

4.1 Patent Stock vs. Flow

The analyses conducted in this study use the "flow" (dummy or volume) of patenting activities in the present year. The patenting activities of firms in Year t (the "flow") may be highly correlated with the innovative capacity of firms (the "stock") in the past years since establishment (Cao and Hsu 2011; Hoenen et al. 2014). Finding did not clearly show whether the firm's patent *stock* or *flow* provides signal to venture capitalists.

To examine the two explanations, we use the patent stock of A-share firms as placebo.[10] *PatentApply_Stock* is the accumulated count of patent applications since incorporation, whereas *PatentGrant_Stock* is the accumulated count of patent granted to the investee by SIPO since incorporation. In untabulated result, we did not find evidence that the patent stock of firms in Year t is positively associated with *VC_Amount* or *VC_Valuation* in year (t+1). This variable only positively predicts *Prob(VC)*.

4.2 Effect of Patent on VC Investment before and after IPO

Our sample includes VC investment events before and after firm's IPO. VC investment in the equity of publicly traded firms (or VIPE) is not a new phenomenon (Chaplinsky and Haushalter 2012). The motives of VC to invest in public firms are beyond the scope of this study, but we can reasonably expect that the value of patents in helping firms access VC funding may differ between public and private firms. This finding is attributed to the fact that going public is a pivotal stage that entails large information disclosure to public investors on a continuous basis. To the extent that patenting activities help reduce information friction between VC and entrepreneurial firm, we expect the positive effect to be stronger when the firm is private rather than when it is public.

The untabulated results show that the coefficient of *ApplyDum* in the *Before IPO* group is statistically larger than that in *After IPO* (Difference is 0.383***, Chi^2=6.68) and only significant in the *Before IPO* group. We also obtain a similar result for *GrantDum*. Using patent counts yields similar results. The coefficient of *PatentApply* is only significantly positive in the *Before IPO* group, whereas group difference is statistically significant. The only exception is the effect of *PatentGrant* on *Prob(VC)*, which is also significant *After IPO*. However, the coefficient's value is statistically smaller than *Before IPO*. Using the *stock* of firm's patent application/grant as alternative independent variable yields similar results. In conclusion, we find that patents help firms obtain VC funding when the firm is young and private. This effect weakens after they go public.

4.3 Long-lasting Effect of Patent Signals

We showed that the patenting activities of firms in previous year have a positive effect on VC investment in the following year. We then examine whether this positive effect is exclusive to the year after (i.e., transient) or whether it can be extended to longer periods (i.e., lasting). This section answers this question using a longer horizon of up to 5 years.[11]

To examine the duration of effect of patent on VC investment persists, we first perform a "year-by-year" test. In the untabulated results, the dependent variables are *Prob(VC)*, *VC_Amount*, and *VC_Valuation* (in Year t). Our independent variables are patent flow measures in Year (t-2), (t-3), (t-4), and (t-5), respectively, with all controls at corresponding years. We find that the positive effect of *ApplyDum* and *GrantDum* on *Prob(VC)* persists in the next five years (all coefficients are significant at the 1% level). The effect of *PatentApply* vanishes after three years, whereas the effect of *PatentGrant* only lasts for one year. Additionally, we find that patents have generally no persistent impact on *VC_Amount,* and the coefficient on *GrantDum* from Years (t-5) to (t-3) are even significantly negative.

Our alternative specification accounts for the possibility that it takes time for venture capitalists to adjust investment decision based on the patent signals of entrepreneurial firm. Following Farre-Mensa et al. (2016), we test whether the patenting activities of firms in Year t can positively predict their probability of obtaining VC investment in the next 2 to 5 years. In the untabulated results, our dependent variable is *Prob(VC)* in the future two, three, four, and five years. We find that this positive effect increases monotonically (both economically and statistically) in the 2- to 5-year window. This finding complements our baseline results.

5. Conclusion

This study presents the first large sample evidence on how patenting activities (applications and grants) help firms finance their growth in China, the world's largest venture capital and technology market outside the U.S. We find that patenting activities in the present year positively predicts the likelihood of firms to obtain VC investment in the following year. Conditional on investment, the quantity and quality of patents improve the amount and valuation of VC investment. This evidence shows that patents serve as positive quality signal to VCs.

By using China as laboratory, we provide evidence on the conditions for which this effect holds. We find that this positive effect is pronounced in the first-round investment, in private firms, in regions with strong protection of intellectual property rights, and during periods of loose monetary policy. These findings support the view that patents are more important in the early stage when information asymmetry between VC and entrepreneur is severe, when the home environment of patentees respects and protects intellectual property rights, and when the market heats up and VCs are chasing investment opportunities.

Our findings that China's state-owned VCs are more sensitive to the patent signal of firms than foreign VCs is consistent with the finding that the government uses its sponsored venture capital to address market failure in supporting technological firms, especially at an early stage. Our finding that corporate VCs are more sensitive to the patent signal of firms than independent VCs suggests that CVCs are technology savvy and highly tolerant of failure. Future research should explore whether high patent sensitivity reflects VC expertise and examine the conditions for which a patent that is sensitive investment strategy leads to high investment returns.

Table 1 Summary Statistics

This table shows the summary statistics for A-share and NEEQ listed firms. The dependent variables are *Prob(VC)*, *VC_Amount*, and *VC_Valuation*. The proxy for patenting activities includes *ApplyDum*, *GrantDum*, *PatentApply*, *PatentGrant*. To show the original distribution in summary statistics and rational coefficients in regressions, we put the primitive value of *PatentApply* and *PatentGrant* and the corresponding standardized value afterwards.

	A-share						NEEQ					
	n	mean	st. dev	min	p50	max	n	mean	st. dev	min	p50	max
Prob(VC)	*27238*	*0.041*	*0.198*	*0*	*0*	*1*	*10103*	*0.085*	*0.279*	*0*	*0*	*1*
VC_Amount	*1005*	*0.454*	*1.465*	*-4.742*	*0.560*	*6.014*	*800*	*7.315*	*1.381*	*0.693*	*7.245*	*12.234*
VC_Valuation	*873*	*6.418*	*1.469*	*-0.117*	*6.553*	*10.961*	*662*	*8.605*	*1.209*	*5.106*	*8.601*	*11.562*
ApplyDum	*27238*	*0.444*	*0.497*	*0*	*0*	*1*	*10103*	*0.188*	*0.391*	*0*	*0*	*1*
GrantDum	*27238*	*0.230*	*0.421*	*0*	*0*	*1*	*10103*	*0.180*	*0.384*	*0*	*0*	*1*
PatentApply	*27238*	*16.677*	*133.922*	*0*	*0*	*6327*	*10103*	*1.810*	*24.57*	*0*	*0*	*1051*
PatentGrant	*27238*	*9.315*	*70.515*	*0*	*0*	*3477*	*10103*	*0.782*	*14.88*	*0*	*0*	*604*
SIZE	*27238*	*21.585*	*1.198*	*19.340*	*21.417*	*25.370*	*10103*	*18.272*	*0.395*	*17.472*	*18.396*	*19.231*
LEV	*27238*	*0.451*	*0.198*	*0.050*	*0.455*	*0.866*	*10103*	*0.408*	*0.063*	*0.271*	*0.437*	*0.555*
TobinQ	*27238*	*2.074*	*1.770*	*0.231*	*1.555*	*10.159*			*N/A*			
Age	*27238*	*2.489*	*0.513*	*0.693*	*2.565*	*7.609*	*10103*	*2.265*	*0.474*	*0*	*2.303*	*4.060*
OperationRisk	*27238*	*0.024*	*0.028*	*0.001*	*0.014*	*0.165*	*10103*	*2.104*	*4.110*	*0.044*	*0.102*	*11.055*
State	*27238*	*0.515*	*0.500*	*0*	*1*	*1*	*10103*	*0.043*	*0.202*	*0*	*0*	*1*
ROA	*27238*	*0.036*	*0.054*	*-0.186*	*0.035*	*0.188*	*10103*	*0.052*	*0.017*	*-0.029*	*0.051*	*0.109*
HighTech	*27238*	*0.382*	*0.486*	*0*	*0*	*1*	*10103*	*0.576*	*0.494*	*0*	*1*	*1*
StageGrowth1	*1005*	*0.146*	*0.354*	*0*	*0*	*1*	*867*	*0.183*	*0.387*	*0*	*0*	*1*
StageGrowth2	*1005*	*0.059*	*0.235*	*0*	*0*	*1*	*867*	*0.796*	*0.403*	*0*	*1*	*1*
Syndicate	*1005*	*1.669*	*1.293*	*0*	*1*	*11*	*867*	*2.353*	*2.418*	*0*	*1*	*16*

Table 2 Paired T-test of firms with and without patenting activities using PSM method

This table shows the results of t-test on *Prob(VC)* in Year (t+1) of firms with patent applications or grants in previous year (treatment group) and those without (control group). We use PSM method to identify matchings between firms with and without patenting activities. First, we estimate a probit model with the dependent variable as dummy of whether firms have patent applications or grants. Our control variables include *State*, *SIZE*, *LEV*, *ROA*, *TobinQ*, *Age*, *PPE*, *R&D*. We then use propensity scores obtained from the first step as basis for Kernel matching (one to many). T values are in parentheses. ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A A-share						
Variable	Sample	Firms with Patent Applications in Year t (Treatment)	Firms without Patent Applications in Year t (Control)	Difference	S.E	T-Value
Prob(VC)	*Unmatched*	*0.059*	*0.026*	*0.033****	*0.002*	*13.55*
	Matched	*0.059*	*0.021*	*0.038****	*0.003*	*11.81*
Variable	Sample	Firms with Patent Grants in Year t (Treatment)	Firms without Patent Grants in Year t (Control)	Difference	S.E	T-Value
Prob(VC)	*Unmatched*	*0.069*	*0.032*	*0.037****	*0.003*	*13.01*
	Matched	*0.069*	*0.030*	*0.040****	*0.004*	*8.90*
Panel B NEEQ						
Variable	Sample	Firms with Patent Applications in Year t (Treatment)	Firms without Patent Applications in Year t (Control)	Difference	S.E	T-Value
Prob(VC)	*Unmatched*	*0.114*	*0.078*	*0.036****	*0.007*	*5.10*
	Matched	*0.114*	*0.102*	*0.012*	*0,033*	*0.37*
Variable	Sample	Firms with Patent Grants in Year t (Treatment)	Firms without Patent Grants in Year t (Control)	Difference	S.E	T-Value
Prob(VC)	*Unmatched*	*0.110*	*0.078*	*0.032****	*0.007*	*4.44*
	Matched	*0.110*	*0.076*	*0.034*	*0.030*	*1.11*

Table 3 Effect of Patenting Activities in Year t on *Prob(VC)* in Year (t+1)

This table shows the results of regression that examines the effects of firm patenting activities in Year t on the *Prob(VC)* in the Year (t+1). All specifications are probit models. The dependent variable is equal to one if the firm receives VC investment in Year (t+1), and zero otherwise. All specifications include industry and year fixed effects. T values are in parentheses. ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Prob(VC) in Year (t+1)							
	A-share				NEEQ			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ApplyDum	0.489***				0.157***			
	(14.33)				(3.20)			
PatentApply		0.024***				0.143***		
		(2.73)				(3.26)		
GrantDum			0.380***				0.095*	
			(11.29)				(1.95)	
PatentGrant				0.026***				0.059***
				(3.00)				(5.02)
SIZE	-0.020	-0.003	-0.023	-0.005	-0.204	-0.205	-0.202	-0.199
	(-1.32)	(-0.23)	(-1.54)	(-0.31)	(-0.73)	(-0.74)	(-0.72)	(-0.72)
LEV	1.316***	1.213***	1.297***	1.215***	0.953	1.049	1.034	0.972
	(13.38)	(12.70)	(13.39)	(12.73)	(0.70)	(0.76)	(0.75)	(0.71)
TobinQ	0.077***	0.071***	0.070***	0.071***	N/A	N/A	N/A	N/A
	(8.48)	(7.95)	(7.84)	(7.95)				
Age	0.222***	0.198***	0.202***	0.197***	-0.075*	-0.083**	-0.074*	-0.079*
	(7.22)	(6.81)	(6.74)	(6.79)	(-1.81)	(-2.00)	(-1.78)	(-1.91)
OperationRisk	-2.012***	-2.233***	-1.992***	-2.230***	-0.001	0.003	0.003	0.004
	(-3.23)	(-3.65)	(-3.25)	(-3.65)	(-0.06)	(0.21)	(0.26)	(0.34)
State	-0.249***	-0.272***	-0.241***	-0.271***	-0.134	-0.128	-0.126	-0.121
	(-7.92)	(-8.77)	(-7.67)	(-8.74)	(-1.37)	(-1.31)	(-1.30)	(-1.25)
ROA	1.142***	1.285***	1.218***	1.281***	0.849	1.189	1.114	1.182
	(3.44)	(3.95)	(3.71)	(3.94)	(0.39)	(0.55)	(0.52)	(0.55)
HighTech	0.094**	0.109***	0.095**	0.111***	-0.051	-0.042	-0.042	-0.035
	(2.47)	(2.92)	(2.51)	(2.96)	(-0.94)	(-0.78)	(-0.79)	(-0.66)
Industry Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
_cons	-2.547***	-2.583***	-2.270***	-2.557***	1.961	1.960	1.867	1.858
	(-8.02)	(-8.40)	(-7.24)	(-8.30)	(0.37)	(0.37)	(0.36)	(0.36)
Pseudo R^2	0.078	0.057	0.069	0.057	0.058	0.061	0.057	0.060
Log lik.	-4.3e+03	-4.4e+03	-4.3e+03	-4.4e+03	-2.8e+03	-2.8e+03	-2.8e+03	-2.8e+03
Chi-squared	609.494	503.258	580.820	503.394	354.003	353.937	351.574	370.507
N	27238	27238	27238	27238	10103	10103	10103	10103

Table 4 Effect of Patenting Activities in Year t on *VC_Amount* in Year (t+1)

This table shows the results of regression that examines the effects of firm patenting activities in Year t on the *VC_Amount* in Year (t+1). All specifications are estimated using OLS with industry and year fixed effects. T values are in parentheses. ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	VC_Amount in Year (t+1)			
	A-share		NEEQ	
	(1)	(2)	(3)	(4)
PatentApply	0.041**		0.021**	
	(2.44)		(2.11)	
PatentGrant		0.031**		0.008**
		(1.97)		(2.11)
SIZE	0.367***	0.370***	-0.449	-0.447
	(7.90)	(8.02)	(-0.65)	(-0.65)
LEV	0.003	0.005	1.561	1.531
	(0.01)	(0.02)	(0.53)	(0.52)
TobinQ	0.030	0.030	N/A	N/A
	(1.09)	(1.11)		
Age	0.273***	0.274***	0.048	0.054
	(3.01)	(3.00)	(0.55)	(0.62)
OperationRisk	1.191	1.202	-0.033	-0.034
	(0.93)	(0.93)	(-1.03)	(-1.04)
State	-0.200**	-0.201**	0.273	0.270
	(-2.35)	(-2.37)	(0.71)	(0.70)
ROA	-1.496	-1.514	-3.351	-3.514
	(-1.55)	(-1.57)	(-0.68)	(-0.71)
HighTech	0.135	0.138	-0.047	-0.040
	(1.40)	(1.43)	(-0.37)	(-0.32)
StageGrowth1	-1.426***	-1.425***	-1.338***	-1.332***
	(-11.08)	(-11.05)	(-2.88)	(-2.87)
StageGrowth2	-0.203	-0.205	-1.582***	-1.585***
	(-0.92)	(-0.93)	(-3.52)	(-3.53)
Syndicate	0.365***	0.367***	0.260***	0.260***
	(10.97)	(11.02)	(12.32)	(12.30)
Industry Effects	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes
_cons	-9.762***	-9.824***	17.046	17.018
	(-10.31)	(-10.45)	(1.35)	(1.35)
F	17.374	17.347	9.386	9.345
Adjusted R^2	0.423	0.423	0.257	0.256
N	1005	1005	800	800

Table 5 Effect of Patenting Activities in Year t on *VC_Valuation* in Year (t+1)

This table shows the results of regression that examines the effects of firm patenting activities in Year t on the *VC_Valuation* in Year (t+1). All specifications are estimated using OLS with industry and year fixed effects. T values are in parentheses. ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	VC_Valuation in Year(t+1)			
	A-share		NEEQ	
	(1)	(2)	(3)	(4)
PatentApply	0.067***		-0.001	
	(2.82)		(-0.04)	
PatentGrant		0.047*		-0.020***
		(1.74)		(-3.02)
SIZE	0.581***	0.586***	-0.355	-0.353
	(14.85)	(15.11)	(-0.51)	(-0.50)
LEV	-0.064	-0.059	1.780	1.772
	(-0.27)	(-0.25)	(0.64)	(0.63)
TobinQ	0.131***	0.133***	N/A	N/A
	(5.42)	(5.46)		
Age	-0.002	-0.001	0.319***	0.325***
	(-0.03)	(-0.02)	(3.53)	(3.59)
OperationRisk	4.792***	4.796***	0.020	0.020
	(4.14)	(4.13)	(0.64)	(0.62)
State	-0.135*	-0.136*	0.373	0.370
	(-1.80)	(-1.81)	(1.36)	(1.35)
ROA	1.748**	1.720**	1.167	1.018
	(2.12)	(2.08)	(0.23)	(0.20)
HighTech	0.197***	0.203***	0.126	0.133
	(2.59)	(2.66)	(1.03)	(1.09)
StageGrowth1	-2.425***	-2.421***	-1.503***	-1.494***
	(-14.92)	(-14.83)	(-3.07)	(-3.05)
StageGrowth2	-0.845***	-0.849***	-1.190**	-1.193**
	(-4.06)	(-4.08)	(-2.57)	(-2.57)
Syndicate	0.062**	0.065**	0.189***	0.189***
	(2.40)	(2.48)	(9.94)	(9.91)
Industry Effects	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes
_cons	-8.326***	-8.442***	14.880	15.065
	(-10.95)	(-11.20)	(1.13)	(1.11)
F	38.297	38.001	8.096	8.123
Adjusted R^2	0.658	0.656	0.262	0.262
N	873	873	662	662

Table 6 Effect of Patent Quality in Year t on *Prob(VC)* in Year (t+1)

This table shows the results of the regression on the impact of patent quality on VC investment in high-tech firms. Panel A shows the analysis on *Prob(VC)*, Panel B shows *VC_Amount* and *VC_Valuation.* We collect the patent quality data from Patentics and limit our sample to high-tech firms. The specifications in Panel A are estimated using Probit model and Panel B OLS model, with industry and year fixed effects. T values are in parentheses. ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A	*Prob(VC)* in Year (t+1)					
	A-share			NEEQ		
	(1)	(2)	(3)	(4)	(5)	(6)
ClaimCount	-0.051			0.040		
	(-1.45)			(0.80)		
ElementCount		0.002			0.061	
		(0.04)			(1.34)	
CitationCount			0.093			-0.065
			(1.64)			(-0.68)
Size	-0.099**	-0.125**	-0.061	-0.115	-0.422	0.957
	(-2.05)	(-2.56)	(-1.00)	(-0.04)	(-0.15)	(0.30)
LEV	1.558***	1.544***	2.022***	29.161	28.684	47.739*
	(6.74)	(6.66)	(5.59)	(1.49)	(1.43)	(1.89)
TobinQ	-0.014	-0.019	-0.008	N/A	N/A	N/A
	(-0.58)	(-0.76)	(-0.21)			
Age	-0.233**	-0.219**	-0.288**	-0.097	-0.099	-0.149
	(-2.54)	(-2.38)	(-2.28)	(-0.89)	(-0.90)	(-0.72)
OperationRisk	1.195	1.191	1.817	0.115	0.108	0.199
	(0.90)	(0.89)	(0.96)	(0.96)	(0.89)	(1.18)
State	-0.300***	-0.291***	-0.359***	-0.488	-0.493	-0.516
	(-3.64)	(-3.49)	(-3.16)	(-1.43)	(-1.44)	(-1.06)
ROA	2.423***	2.342***	2.936***	-8.954	-9.391	-17.647
	(3.06)	(2.95)	(2.64)	(-0.83)	(-0.84)	(-1.27)
Industry Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes
_cons	-0.097	0.479	-0.933	-9.198	-3.491	-34.325
	(-0.09)	(0.43)	(-0.67)	(-0.19)	(-0.07)	(-0.56)
Pseudo R^2	0.066	0.064	0.086	0.057	0.058	0.108
Log lik.	-797.202	-789.283	-389.092	-420.628	-419.515	-149.462
Chi-squared	113.561	103.457	76.867	49.781	51.560	40.518
N	3503	3466	1856	1356	1350	413

Panel B	*VC_Amount* in Year (t+1)						*VC_Valuation* in Year (t+1)					
	A-share			NEEQ			A-share			NEEQ		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
ClaimCount	-0.024			0.049			0.026			0.070		
	(-0.29)			(0.49)			(0.39)			(0.72)		
ElementCount		0.016			0.018			-0.032			-0.016	
		(0.19)			(0.16)			(-0.59)			(-0.16)	
CitationCount			0.250			-0.164			0.345*			-0.059
			(1.25)			(-0.72)			(1.67)			(-0.41)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
_cons	-11.324***	-10.546***	-18.020***	21.621	31.381	-19.880	-8.424***	-9.099***	-8.148***	-8.106	-2.347	-21.432
	(-5.12)	(-4.54)	(-5.65)	(0.50)	(0.74)	(-1.38)	(-5.31)	(-5.39)	(-4.38)	(-0.24)	(-0.07)	(-1.32)
F	6.443	6.136	4.877	5.216	5.196	5.258	15.078	14.627	11.644	4.604	4.552	3.460
Adjusted R^2	0.400	0.390	0.482	0.363	0.362	0.582	0.661	0.657	0.658	0.366	0.363	0.486
N	213	210	101	127	127	50	189	186	139	107	107	40

Table 7　Effect of Patent Quantity on *Prob(VC)* Conditioning on Patent Quality

This table shows the regression results of the impact of patent quantity on VC investment and conditioning on patent quality in high-tech industry of A-share firms. Patent quality data are obtained from Patentics and we limit the sample to high-tech firms. The dependent variable is *Prob(VC)* in year t+1. "High Patent Quality" group is defined as the sample whose *ClaimCount* is larger than the industry-year median, *ElementCount* is smaller than the industry-year median, and *CitationCount* is larger than the industry-year median, otherwise they are defined as "Low Patent Quality" group. All the controls are similar to that in Tables 3 to 5, which we omit for brevity. The specifications in Panel A are estimated using a probit model and Panel B using OLS model with industry and year fixed effects. T values are in parentheses. ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Prob(VC) in Year (t+1)											
	A-share											
	High Patent Quality			Low Patent Quality			High Patent Quality			Low Patent Quality		
	ClaimCount	ElementCount	CitationCount	ClaimCount	ElementCount	CitationCount	ClaimCount	ElementCount	CitationCount	ClaimCount	ElementCount	CitationCount
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
PatentApply	0.177**	0.013	0.007	0.009	0.010	0.033						
	(2.31)	(1.07)	(0.92)	(0.87)	(0.66)	(1.26)						
PatentGrant							0.035*	0.116*	0.037**	0.031	0.083	0.044
							(1.83)	(1.78)	(1.99)	(1.58)	(1.58)	(1.22)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
_cons	-1.249	-1.851*	-0.691	0.030	0.616	-0.217	-0.938	-1.630	-0.465	-0.082	0.880	-0.201
	(-1.19)	(-1.66)	(-0.71)	(0.02)	(0.50)	(-0.13)	(-0.90)	(-1.47)	(-0.48)	(-0.06)	(0.71)	(-0.12)
Pseudo R^2	0.040	0.031	0.026	0.039	0.044	0.079	0.042	0.032	0.028	0.036	0.045	0.079
Log lik.	-450.618	-443.857	-606.328	-402.158	-410.922	-243.118	-449.803	-443.381	-605.626	-403.437	-410.317	-243.117
Chi-squared	34.146	27.585	35.241	36.139	47.966	40.982	36.573	28.675	38.564	34.104	49.898	40.696
N	2119	2024	2966	1921	2016	1074	2119	2024	2966	1921	2016	1074

Table 8 The Impact of Intellectual Property Rights (IPR) Protection

This table shows the results of regression that examines the effects of IPR protection on the relation between patenting activities in Year t and *VC_Amount / VC_Valuation* in Year(t+1). IPR protection is measured by the size of technological market, which is defined as the percentage of provincial transaction volume of technology transfer to a province's GDP. LowIPR is a dummy variable that is equal to one if the IPR protection in the firm's home province is less than the median of all provinces across the country. All the controls are the same as those in Tables 4 to 5, which we omit for brevity. All specifications are estimated using OLS with industry and year fixed effects. T values are in parentheses. ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels.

	VC_Amount in Year(t+1)				*VC_Valuation* in Year(t+1)			
	A-share		NEEQ		A-share		NEEQ	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LowIPR	-0.129	-0.134*	-0.181*	-0.184*	-0.042	-0.039	0.015	-0.003
	(-1.64)	(-1.69)	(-1.86)	(-1.90)	(-0.64)	(-0.60)	(0.17)	(-0.03)
PatentApply	0.051***		0.074***		0.071***		0.114***	
	(4.23)		(4.67)		(3.05)		(5.93)	
PatentApply*LowIPR	-0.339***		-0.057***		-0.170*		-0.136***	
	(-2.66)		(-3.06)		(-1.83)		(-6.71)	
PatentGrant		0.036**		0.157		0.052*		0.651*
		(2.43)		(0.47)		(1.83)		(1.93)
PatentGrant*LowIPR		-0.192*		-0.149		-0.161**		-0.675**
		(-1.84)		(-0.44)		(-1.98)		(-2.00)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
_cons	-9.510***	-9.374***	18.057	18.023	-8.842***	-8.965***	15.749	16.217
	(-8.97)	(-8.87)	(1.44)	(1.43)	(-10.84)	(-11.02)	(1.16)	(1.21)
F	19.243	16.469	8.997	8.939	36.863	36.679	7.781	7.802
Adjusted R^2	0.430	0.427	0.259	0.258	0.659	0.658	0.264	0.265
N	1005	1005	800	800	873	873	662	662

Table 9 Impact of VC Type

This table shows the results of the regression that examines the effects of patenting activities of firms on *VC_Amount / VC_Valuation*, conditioning on VC type. SVC is a dummy variable that is equal to one if the controlling shareholder of the VC institution is government or its affiliates, and zero if the controlling shareholder is foreign organizations or individuals. IVC is a dummy variable that is equal to one if the VC firm is managed by general partner (GP) and not affiliated to any industrial firms, bank, or insurance company, and zero otherwise. All controls are the same as those in Tables 4 to 5, which we omit for brevity. All specifications are estimated using OLS with industry and year fixed effects. T values are in parentheses. ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A	*VC_Amount* in Year (t+1)				*VC_Valuation* in Year (t+1)			
	A-share		NEEQ		A-share		NEEQ	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SVC	-0.724***	-0.688***	-0.204	-0.202	-0.358***	-0.329**	-0.199	0.200
	(-4.90)	(-4.61)	(-0.42)	(-0.42)	(-2.66)	(-2.44)	(-0.66)	(0.64)
PatentApply	-0.561**		0.018		-0.075		4.385**	
	(-2.04)		(1.45)		(-0.30)		(2.46)	
PatentApply*SVC	0.599**		-0.317		0.099		-4.152	
	(2.17)		(-1.09)		(0.40)		(-1.36)	
PatentGrant		-0.056**		0.019*		0.134		1.166***
		(-2.23)		(1.85)		(0.69)		(3.13)
PatentGrant*SVC		0.082		1.334***		-0.127		0.347**
		(0.35)		(4.42)		(-0.65)		(2.30)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
_cons	-8.299***	-7.748***	46.307	50.090	-6.772***	-6.675***	59.014*	48.179
	(-4.68)	(-4.40)	(0.99)	(1.05)	(-4.57)	(-4.54)	(1.91)	(1.47)
F	6.627	6.427	2.556	2.764	17.175	17.142	2.726	3.194
Adjusted R^2	0.387	0.379	0.225	0.248	0.672	0.672	0.286	0.338
N	366	366	178	178	324	324	143	143

Panel B	VC_Amount in Year (t+1)				VC_Valuation in Year (t+1)			
	A-share		NEEQ		A-share		NEEQ	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IVC	0.010	0.011	-0.021	-0.020	-0.044	-0.047	-0.029	0.015
	(0.13)	(0.14)	(-0.21)	(-0.20)	(-0.68)	(-0.72)	(-0.33)	(0.17)
PatentApply	0.053***		0.096		0.063***		0.551**	
	(4.35)		(0.48)		(3.40)		(2.13)	
PatentApply *IVC	-0.192*		-0.079		-0.012		-0.555**	
	(-1.70)		(-0.40)		(-0.17)		(-2.14)	
PatentGrant		0.041**		0.916***		0.044***		1.125***
		(2.03)		(4.74)		(2.78)		(5.91)
PatentGrant *IVC		-0.150*		-0.904***		0.006		-1.142***
		(-1.91)		(-4.70)		(0.11)		(-6.03)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
_cons	-9.942***	-10.035***	25.184**	25.336**	-9.216***	-9.313***	18.319**	19.175**
	(-8.70)	(-9.23)	(2.49)	(2.50)	(-10.18)	(-10.27)	(2.38)	(2.48)
F	18.131	16.600	9.153	9.265	34.927	34.689	7.764	7.921
Adjusted R^2	0.390	0.390	0.267	0.270	0.614	0.612	0.266	0.271
N	1003	1003	783	783	877	877	653	653

References

Acharya, V.V. and L.H. Pedersen, 2005, Asset pricing and liquidity risk, Journal of Financial Economics 77(2), pp. 375-410.

Andrieu, G., and A.P. Groh, 2012, Entrepreneurs' financing choice between independent and bank-affiliated venture capital firms, Journal of Corporate Finance 18(5), pp. 1143-1167.

Ang J.S., Cheng Y., and Wu C.P., 2014, Does enforcement of intellectual property rights matter in China? Evidence from financing and investment choices in the high-tech industry, Review of Economics and Statistics 96(2), pp. 332-348.

Bottazzi, L., Da Rin, M., and Hellmann, T., 2009, What is the role of legal systems in financial intermediation? Theory and evidence, Journal of Financial Intermediation 18, pp.559–598.

Bottazzi L., Da Rin M., and Hellmann T., 2016, The importance of trust for investment: Evidence from venture capital, Review of Financial Studies 29(9), pp. 2283-2318.

Brav A., Jiang W., Ma S., and Tian X., 2016, How does hedge fund activism reshape corporate innovation?, National Bureau of Economic Research Working Paper.

Cao J.X., and Hsu P.H., 2011, The Information Role of Patent in Venture Capital Financing, Working Paper.

Chaplinsky S., and Haushalter D., 2012, VIPI financing: venture capital investments in pubic equity, in Cumming D. (Eds.), The Oxford Handbook of Venture Capital. (Oxford University Press, Oxford).

Chemmanur T.J., Loutskina E., and Tian X., 2014, Corporate venture capital, value creation, and innovation, Review of Financial Studies 27(8), pp. 2434-2473.

Cochrane J., 2005, The risk and return of venture capital, Journal of Financial Economics 74, pp. 3-52.

Conti A., Thursby J., and Thursby M., 2013, Patents as Signals for Startup Financing, The Journal of Industrial Economics Volume LXI, pp. 592 – 622.

Da Rin M., Hellmann T.F., and Puri M., 2011, A Survey of Venture Capital Research, TILEC Discussion Paper No. 2011-044.

Engel D., and Keilbach M., 2007, Firm-level Implications of Early Stage Venture Capital Investment-An Empirical Investment, Journal of Empirical Finance14(2), pp. 150-167.

Fama E., and French K., 2004, New listings: fundamentals and survival rates, Journal of Financial Economics 72, pp. 229-269.

Farre-Mensa J., Hegde D., and Ljungqvist A., 2016, Do patents facilitate entrepreneurs' access to venture capital?, Working Paper.

Fulghieri P., and Sevilir M., 2009, Organization and financing of innovation, and the choice between corporate and independent venture capital, Journal of Financial and Quantitative Analysis 44(6), pp. 1291-1321.

Gans J.S., Hsu D.H., and Stern S., 2008, The impact of uncertain intellectual property rights on the market for ideas: Evidence from patent grant delays, Management Science 54(5), pp. 982-997.

Gompers P., 1995, Optimal investment, monitoring, and the staging of venture capital, Journal of Finance 50(5), pp. 1461-1489.

Gompers P., Kovner A., Lerner J., and Scharfstein D., 2004, Venture capital investment cycles: the impact of public market, Journal of Financial Economics 87(2008), pp. 1-23.

Guo, D., and K. Jiang, 2013, Venture capital investment and the performance of entrepreneurial firms: evidence from China, Journal of Corporate Finance 22, pp. 375-395.

Gupta U., 2000, Done Deals: Venture Capitalists Tell Their Stories. (Harvard Business School Press, Boston).

Hellmann T., and Puri M., 2002, Venture capital and the professionalization of start-up firms: empirical evidence, The Journal of Finance 57(1), pp. 169-197.

Hellman T, and Puri M., 2000, The interaction between product market and financing strategy: the role of venture capital, Review of Financial Studies 13(4), pp. 959-984.

Hirukawa M., and Ueda M., 2008, Venture capital and innovation: which is first?", CEPR Discussion Paper 7090, Available at SSRN: https://ssrn.com/abstract=1242698 (last visit Dec. 12, 2017).

Hoenen S., Kolympisis C., Schoenmakers W., and Kalaitzandonakes N., 2014, The diminishing signaling value of patents between early rounds of venture capital financing, Research Policy 43(6), pp. 956-989.

Hoening D., and Henkel J., 2015, Quality signals? The role of patents, alliances, and team experience in venture capital financing, Research Policy 44(5), pp. 1049-1064.

Hsu D.H., and Ziedonis R.H., 2013, Resources as dual sources of advantage: implications for valuing entrepreneurial-firm patents, Strategic Management Journal 34(7), pp. 761-781.

Hsu P, Tian X., and Xu Y., 2014, Financial development and innovation: cross-country evidence. Journal of Financial Economics 112(1), pp. 116-135.

Kortum S., and Lerner J., 2000, Assessing the contribution of venture capital to innovation, Rand Journal of Economics 31, pp. 674-692.

Lerner J., and Schoar A., 2005, Does legal enforcement affect financial transactions? The contractual channel in private equity, Quarterly Journal of Economics 120, pp. 223-246.

Nahata R., Hazarika S., and Tandon K., 2014, Success in global venture capital investing: Do institutional and cultural differences matter? Journal of Financial and Quantitative Analysis 49(4), pp. 1039-1070.

Scharfstein D.S., and Stein J.C., 1990, Herd behavior and investment, American Economic Review 80, pp. 465–479.

Spence M., 1973, Job market signaling, The Quarterly Journal of Economics 87(3), pp. 355-374.

Stuart T.E., Hoang H., and Hybels R., 1999, Interorganizational endorsements and the performance of entrepreneurial ventures, Administrative Science Quarterly 44, pp. 315–349.

Tian X., 2011, The causes and consequences of venture capital stage financing, Journal of Financial Economics 101(1), pp. 132-159.

Tian X., and Ye K., 2017, How does policy uncertainty affect venture capital?, Working Paper, Available at SSRN: https://ssrn.com/abstract=2910075.

[1] We provide the institutional settings in detail in the online Appendix due to article length limit.

[2] Note that CSMAR provides the (albeit incomplete) financial information of A-share firms three years before IPO. For NEEQ firms, there is no public dataset that provides their financial information before listing. To account for this financial data limitation *before* listing and following VC literature (Gompers 1995; Tian and Ye 2017), we use the industry-year average of financial variables for *public* firms in A-share and NEEQ market to replace the missing variables. This approach is consistent with the idea that when VC considers the quality of investment projects, they tend to use public firms in the same industry-year as benchmark. To be sure, we use the actual reported financial variables of our sample firms in all regressions *after* listing.

[3] Technology-intensive industries include CSRC industry codes C26, C27, C28, C30, C35, C38, C39, I, M.

[4] In the robustness tests (see 4.7.3), we report the results for longer time span and show that they are qualitatively similar.

[5] *ClaimCount* is the average count of claims at filing of a patent application. A larger value means wider scope of patent protection and, hence, better quality of the patent. *ElementCount* is a discretely claimed component of a patent claim. In general, this variable is inversely proportional to the scope of a patent claim. *CitationCount* is the average count of citation for a patent application cited by other patent applications. Higher value indicates better patent quality.

[6] We use the following method to measure the tightness of monetary policy:

$$MP = \frac{\Delta M_2}{M_2} - \left(\frac{\Delta GDP}{GDP} + \frac{\Delta CPI}{CPI}\right),$$

where $\Delta M_2 / M_2$ is the growth rate of money supply (M2), $\Delta GDP/GDP$ is the GDP growth rate in China, indicating the economic development across the country, $\Delta CPI/CPI$ is the growth rate of Consumer Price Index, indicating the change of price level. We treat the sample with MP<0 as the Tight Monetary Policy period, otherwise, we treat it as Loose Monetary Policy period.

[7] We define state-owned VCs as the controlling shareholder of the VC institution in Chinese the government, state-owned enterprise, or its affiliates.

[8] Following Fulghieri and Sevilir (2009) and Andrieu and Groh (2012), we identify IVC as VC firms managed by a general partner (GP) and not affiliated to any industrial firms, banks, insurance companies, or other type of institutional investor.

[9] We provide robustness test results in an online Appendix due to article length limit.

[10] Given that NEEQ firms are mostly young, there is little difference between their patent stock and flows.

[11] To account for the data availability up to 5 years before investment, this test includes A-share firms only and excludes NEEQ firms.